Industrial Engineering Journal
ISSN: 0970-2555
Volume : 49, Issue 7, No. 1, July : 2020

SVM AND KNN TECHNIQUES IN A MIXED MODELS AUTOMATED SYSTEM FOR DETECTING DIABETIC RETINOPATHY

V.Praveen Kumar, N.Kesav Kumar, P.Suseela, Dept of Electronics and Communication Engineering, Sree Venkateswara College Of Engineering, Nellore (Dt), Andhra Pradesh, India.
Modem.Jeevan Kumar, Dept of Computer Science and Engineering, Sree Venkateswara College Of Engineering, Nellore (Dt), Andhra Pradesh, India.

ABSTRACT
Diabetes is a fixed condition of the eyes known as diabetic retinopathy (DR). If the excessive glucose levels aren't managed throughout this condition, the retina will suffer gradual damage. Proliferative diabetic retinopathy (PDR) and Non-proliferative diabetic retinopathy (NPDR) are two different types of DR. In this study, we provide a robust automatic method that recognises and categorises the various stages of DR. Following the processes of pre-processing, feature extraction, and feature categorization is the desired job.The data extraction stage only gathers relevant characteristics, the preliminary processing phase enhances the presence of anomalies and division, and the classification stage makes use of classifiers like the support vector machine (SVM), K-nearest neighbour (KNN), and binary trees. (BT). In addition, the outcomes of the classification process using the random forest classifier are compared. Multiple disease severity grading databases were used to accomplish this, yielding accuracy rates of 98.06%, sensitivity rates of 83.67%, and specificity rates of 100%.

Keywords*:* Support Vector Machine (SVM), K-nearest neighbour (KNN), BinaryTree (BT), Random Forest classifier (RFC), Database (Drive)

1. INTRODUCTION

A condition of the eyes that affects diabetics primarily is known as diabetic retinopathy.Over 290 million people around the world and 69.2 million people in India have been impacted by this serious illness. In the upcoming years, the rate at which people are afflicted will drastically expand.The illness is related to the focus of the attention and, if at all undiscovered, may have negative repercussions on the patient. Diabetic Retinopathy develops when the retina's blood vessels leak fluid into the retina, causing exudates to form there.The diabetic patient may lose their vision as a result.For people with DR, microaneurysms, exudates, and haemorrhages are the main causes of visual loss.Blood vessels expand within the retina, and the severity of the eyesight loss also worsens.
The following are the photographs of healthy retina and diabetic retinopathy retina.

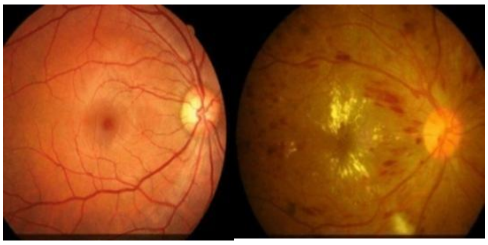
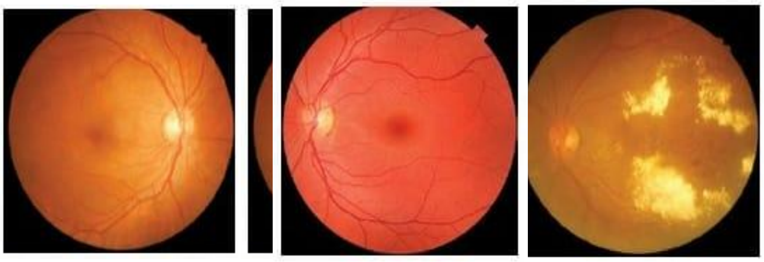


Fig: a. Healthy Retina b. Diabetic Retinopathy Retina

There are two stages of DR :
There are two types of diabetic retinopathy: proliferative (PDR) and non-proliferative (NPDR).
The retina and blood arteries operate normally at the PDR level, and the optic disc is clear. The NPDR level is thought to be the first stage of DR, and the degree of severity of its abnormalities (mild, moderate, and severe) are classified. At this stage, the retina's tiny veins (blood vessels) start to leak blood or fluid into the tissue, which causes the lens to store exudates that. Disorders often include haemorrhages, exudates, and

microaneurysms because the skin becomes wet and irritated.

Period of diabetic retinopathy:



a.) No DR b.) Mild DR c.) Moderate DR d.) Severe DR

Early diagnosis of the illness might lead to swiftly obtaining medical assistance. The automatic review of the photographs would enable the medical professionals to more precisely and quickly determine the patient's status. As a result, where manual visual evaluation and observation are needed, other ways are frequently just as effective. Using the proper image processing techniques, we focused on determining retinal images in this research. With this, it will be simple to distinguish between normal and abnormal retinal pictures, which may result in less reviews for the physicians.

2. RELATED WORK

The Global Clinical Diabetic Retinopathy (ICDR) scale, which includes a 5-Point rating for diabetic retinopathy as examples typical, mild, moderate, severe, and proliferative, is one of the most widely used clinical measures. Many AI algorithms use this classification developed by ICDR to comprehend the severity of diabetic retinopathy (DR).

According to recent assessments, there are over 40 million diabetics in India, and as a result, the majority of the population is rife with DR. Early identification frequently saves 90% of DR patients. Both human and automated methods can be used to prevent and identify DR. A manual method could take a long time. Ophthalmologists must be skilled in the field of work throughout this procedure. The development of ophthalmology in the present has made it possible for AI to diagnose and treat a variety of disorders, including retinopathy brought on by diabetes. The inventor of this solution advised combining the reviews of diabetic retinopathy (DR) and diabetic macular edoema (DME) in this review.

Two small picture datasets with manually labelled lesions were used for the automatic identification of microaneurysms and exudates. With the help of a large database that contains both diseased and normal pictures and distinguishes between manual gradings, the computer-assisted diagnostic method for the grading and identification of diabetic retinopathy and macular edoema (ME) hazards was enhanced.

Although the suggested method did not produce high accuracy, it did shorten the time required to consume a lot of information. The identification of blood vessels in retinal pictures is plagued by the existence of both dark and brilliant lesions. The segmentation of blood arteries plays a crucial part in the processing stage of the identification of dark and bright lesions.

Lam B.S. et al. created the locally normalised concavity measure in accordance with adjustments of spherical intensity with the aim of overcoming the unevenly distributed noise. Additionally, the perception of Weber's law was accustomed map input images for robust vessel segmentation. The obtained findings showed that the recommended approaches performed well on both normal and pathological retinal pictures.

3. METHODOLOGY:

The methodology follows a less complicated approach than the present one.

One of the many uses for pattern recognition techniques is the diagnosis of diabetic retinopathy. One may classify pattern recognition as a categorization job. Pattern recognition offers helpful data backed by observations. We would want to map from the measurement space into a meaningful space, where various points have various meanings, to design a pattern detection system. Pre-processing, feature extraction and

selection, design and optimisation of the classifier, and optimisation of the classifier are the core elements of a pattern recognition system.
Therefore, the three main steps of our suggested method for recognising diabetic retinopathy are pre-processing, feature extraction, and have classification, followed by identification of diabetic retinopathy. The following is the diagram.
A detail information is discussed below:

PREPROCESSING
To enhance the provided fundus picture, pre-processing is done. It then employs the succeeding techniques, such as adaptive histogram equalisation, contrast stretching, and a median filtering approach.
Changing the colour of a picture is the first stage in pre-processing. RGB is the format for the retinal input picture. Due to the 224 colour components that make up the RGB colour space, it is quite difficult to evaluate each colour separately. Therefore, we intended to apply a pre-processing step that is applied within the fundus image's luminance, chrominance blue CB, and chrominance red CR colour spaces.
In order to convert an RGB image to a YCbCr image, it combines two of the RGB's spectral colour components to create the intensity (Y). To apply the median filtering technique, the Y constituent is detached from the YCbCr picture. Then, contrast stretching and intensity normalisation are frequently used.
Later, as described in the algorithm subsection, the image is acquire to RGB (as an inverse transform of YCbCr).

FEATURE EXTRACTION
The retinal picture will be used to extract exudates, microaneurysms, and haemorrhages based on colour, intensity, and texture. In order to distinguish them, we attempt to extract these pertinent and important elements from the fundus picture. The pre-processed picture is sent into the intense and red lesion perception algorithms, which then execute the attribute activity procedure on the locations that have been discovered. The feature extraction process is performed as said above.

FEATURE CLASSIFICATION:
Once obtaining the characteristics using the detection methods, the feature classification process is started utilizing classifiers like SVM, BT, KNN, and RFC. To examine fundus screening, a combination of image analysis and machine learning methods is frequently used.
The retinal fundus image characteristics are often extracted throughout this process using methods for image processing. A learning model for categorization is created using machine learning methods, and this classification can detect the existence (or absence) of the disease in retinal fundus images. The fundus images in the current work are initially categorized into three classes using three device-learning-based methods.
In order to obtain the final conclusions backed by the greatest amount of votes for each classifier, the output of the classifier is afterwards used as input to a voting mechanism.

THE ALGORITHMIC PROGRAM OF THE PROJECTED TECHNIQUE
The projected work technique is as follows:
Pre-processing step:
It's the beginning stage of the proposed work. The noise that was added to the fundus images during generation and transmission is eliminated in this step, along with the identification of the MAs. The sequence of steps that we adhere to is as follows:
Apply the median filter, stretch the contrast, normalise the intensity, convert the image from RGB to YCbCr while keeping only the Y part, recover the YCbCr, and then restore the YCbCr back to RGB.
Discernment of the red lesion:

This section outlines every computational step required for the identification of haemorrhages, in the order described below:
Maintain adaptive classification with dark background polarity and a sensitivity value of 0.15; collect the divided characteristics, extents, and aspect ratio; and filter out the segmented picture according to extent and aspect ratio.
• Extraction of red lesion features: This section outlines every processing step required to extract features from the red lesion in the following order:
Get all-region characteristics, count the number of areas in the first feature, measure the average area and perimeter of every area in the second feature, calculate the average solidity of all the areas in the fourth characteristic, and then stack every feature together.

Discernment of luminous lesion:

The first part outlines every processing step required for the identification of haemorrhages, and we subsequently go through the stages in a particular order:
Retain adaptive segmentation using sensitivity 0.15 and dark foreground polarity Obtain the characteristics, extents, and aspect ratio of the segmented picture Remove the segmented image based on extend and component ratio
Identifying red lesion features This section outlines every processing step required for obtaining the red lesion's features in the order that we do so:
Get all-region properties, count the number about regions in the first feature, measure the mean dimension of all the regions in the second characteristic, the mean perimeter of everything the regions in the third feature, and the mean durability of all the regions in the fourth feature. Then, stack every feature together.

Fusion:

The last portion in the pre-processing step is Fusion. Following the red and white lesion extraction of features procedure is finished, this sort of segmentation step is used..

Classifiers Description:

Support Vector Machine:

The method Support Vector Machine (SVM), which was created for pattern categorization, has lately been modified for use in various applications, such as discovering regression and distribution estimates. It is now a very active study subject at several universities and research institutes, including the National University of Singapore (NUS) and Massachusetts Institute of Technology (MIT). It has been used in numerous domains, such as bioinformatics. Although the SVM is used to solve many different optimisation problems, including regression, knowledge classification remains its most well-known application. The key concept is discussed. The objective is to locate a hyper-plane that separates the info points by a maximum margin. The info points are classified as positive or negative.

Data Classification KNN Classifier:

Evelyn Fix and Joseph Hodges developed the k-nearest neighbours algorithm (k-NN), a non-parametric supervised training method, in 1951. Thomas Cover later enhanced it. It is used for regression as well as classification. In both cases, the input consists of the k nearest training examples from a huge data collection. The outcomes will vary depending on whether k-NN is applied for categorization or regression: • The output of k-NN classification could be a class membership. It is consequently classified by the majority of its closest neighbours, with the item being assigned to the class that is most common among its k nearest neighbours (k may be a positive integer, frequently a small number). If k = 1, In k-NN regression, however, the item's value of the property is the output, and the item is only designated as a category of that one nearest neighbour. The mean values of the k closest neighbours are represented by this value.

Binary Tree:

With no more than two children for each parent, a binary tree is a sort of non-linear organisation. In addition to the information element, each node in a very binary tree also has a left and right reference. A foundation node is the node at the top of a tree's hierarchy. Parent nodes are those that are capable of holding sub-nodes. As well as being named a strict binary tree, the full binary tree has that designation. Each node of the tree must have either 0 or 2 offspring in order for it to be regarded a full binary tree. It is even possible to define the whole binary tree since all nodes inside the tree, excluding the leaf nodes, must have two children.

Random Forest Algorithm:

The Random Forest Algorithm uses a variety of decision trees, each having the same nodes but producing different leaves based on the input data. To find a solution that reflects the common of these decision trees, it combines the choices of several decision trees. The random forest technique utilises labelled data to "learn" how to categorise unlabeled data, making it a possible example of a supervised learning model. This is frequently used as an alternative to the K-means Cluster method, which was described as an unsupervised learning model in a previous article. The Random Forest Algorithm is a versatile model that is frequently used by engineers since it can be used to handle both regression and classification issues.

EXECUTION METRICS includes : The effectiveness of the research project as a whole is evaluated using precision, specificity, sensitivity, and F1-score measures. The accuracy of each model is determined by dividing the total number of labels correctly identified by the total amount of images in every category, which follows from Equations (1) to Equations (2) (6).

$$Sensitivity(SEN) = TP/TP + FN \quad (1)$$

$$Specificity(SPE) = TN/TN + FP \quad (2)$$

$$Accuracy = TP + TN/TP + TN + FP + FN \quad (3)$$

$$F1 - Score = 2 * Precision * Recall\ Precision + Recall \quad (4)$$

$$where\ Precision = TP/\ TP + FP \quad (5)$$

$$Recall = TP/TP + FN \quad (6)$$

While FP is the total amount of false-positive instances, FP is the amount of false-negative cases, FN is the amount of false-positive cases, TP is the amount the true cases, and TN is the amount of true negative cases.

TRAINING AND TESTING

The exudates and bleeding zones are where the features are retrieved when the training process is started by pre-processing the complete training. The target classes each feed one of the three classifiers with all the training characteristics they have collected from all the photos. The classifiers are then set aside for testing.

Similarly, the pre-processing stage also starts the testing procedure. The prediction values of each classifier are also taken into account as votes, and the mode of votes is determined. The upper vote then decides on categorization. The parameters for the used classifiers are established, and as a result, the fitness functions are explained. At the training stage, it is possible to store the characteristic vectors and class labels of the training samples. Euclidean distance is a common distance measure for continuous variables.

Another measure, such as the overlap metric (also known as the Hamming distance), is frequently employed for distinct variables, including text categorization. For instance, k-NN is used by correlation coefficients like Pearson and Spearman as a measure in the context of organic phenomena microarray data. When the category distribution is skewed, the fundamental "majority voting" categorization suffers a disadvantage. Examples of a more common class likely to dominate the forecast of the fresh instance due to their tendency to be common amongst the k nearest neighbours owing of their size. By weighing the categorization and taking into consideration the distance among the test site and each of its k nearest neighbours, this problem can be solved. The grouping (or value in regress problems) of each of the k nearest points increases by a weight that is inversely related to the distance from that point to the test point. A novel approach to dealing with skew may involve the use of abstractions in the representation of data.

Without respect to their density in the initial training data, every node in a self-organizing map (SOM), each node may be a representation (a centre) of a cluster of corresponding points.

The SOM can then be subjected to KNN.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 49, Issue 7, No. 1, July : 2020

Training algorithm

As a consequence, we go forward in the following order: considering the quantity of coaching images, retrieve the it image for i D 1 from the database. Pre-processing and feature extraction applications, Assign a Target Class Allowed by the Dataset Severity and stack the feature results to the training image array. Creating classifiers as this sub-segment outlines the steps necessary to train a particular classifier, the subsequent classifiers are selected to perform the operations: The BT classifier, the KNN classifier, and the SVM classifier should all be trained.

Testing algorithm

Since this segment outlines the general processes required for foreseeing the results through the feature extraction process using the designated classifier, this process is used: As instructed, obtain the test image. • Use picture pre-processing and feature extraction, Obtain the model of the three predicted outcomes. Anticipate the features of the SVM classifier, the BT classifier, the KNN classifier, and furthermore. The brilliant lesion identification algorithm is provided, which uses an adaptive threshold and filtering mechanism to perform the morphological operation. The application tries to identify the red lesions as the reverse region by pre-processing them to produce low-intensity values (relatively). The red lesions and bright method, however, are similar aside from sensitivity. By employing a side ratio limit, the anomaly rejecting technique may discriminate between the recovered vein (shown inside the red portions), and the approach can also widen the threshold so as to enable the tested object to be filled on its related bounding box. The categorization is created by calibrating the remaining features:

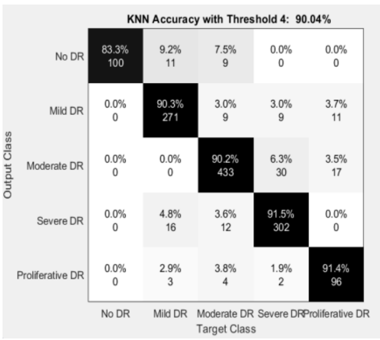
1) Identify the objects that were found.

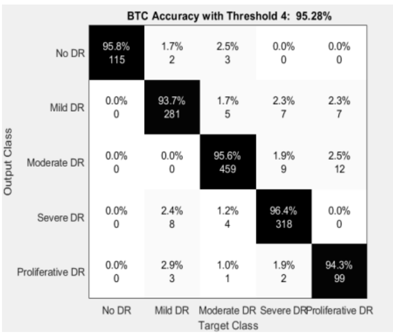
2) Each identified object's mean area, maximum area, diameter, and solidity were determined.

It is significant to note that the method generates three sets of characteristics, that are lexicographically ordered vertically and are categorised as red, brilliant, and fused characteristics associated with red and bright regions. However, the fused features have been chosen to carry out the remaining classification. The three classifiers that are trained to fulfil the classification task are SVM, KNN, and BT. Voting is used to determine the final outcome (a maximum votes for every classification output). The classification considered the subsequent five sensitivity levels: 1) No DR 2) Poor DR Third, a medium DR spread-related DR; Severe DR; and DR.The number of labels that were correctly assigned relative to the total number of pictures in to each one class is used to calculate each model's accuracy.

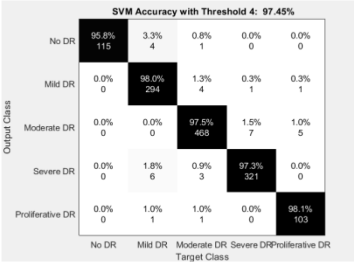
Experimental Analysis

The following are the confusion matrices which shows the experimental analysis of each of the classifiers.

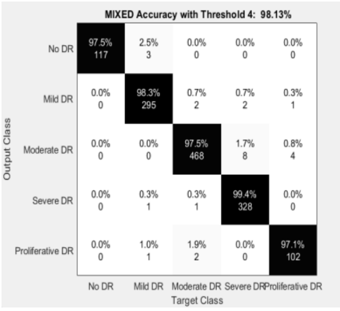


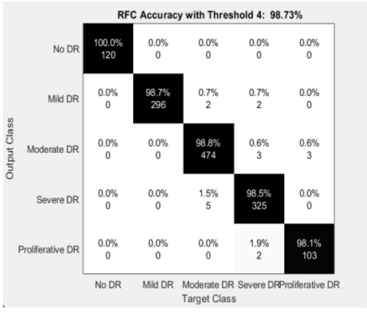


KNN MATRIX **BTC MATRIX**



SVM MATRIX

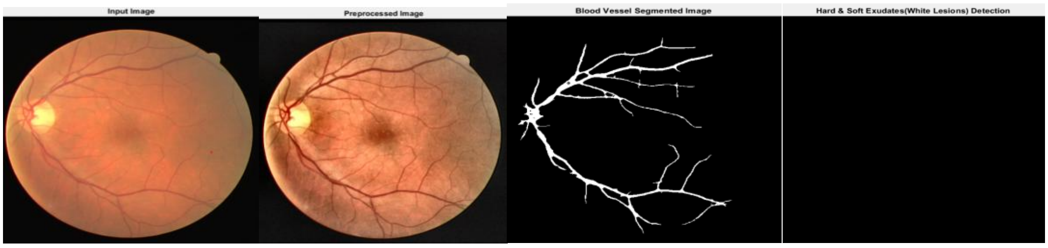




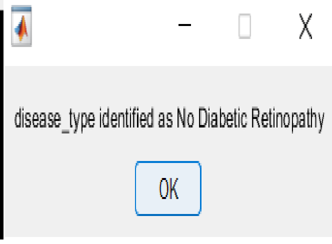
MIXED MODEL MATRIX **RFC MATRIX**

RESULTS AND DISCUSSION

The Mat lab programming environment was used for all of the studies. We made use of a 16 GB RAM computer with a 1TB SSD and an Intel Core i7 7th generation CPU. In this part, we emphasise the main outcomes of the classifier results, time complexity, and picture pre-processing. The suggested work is contrasted with traditional approaches in a separate presentation.



Input image Preprocessed image Blood vessel segment detection Hard and Soft exudates image detection



Microaneurysms and haemorrhages detection Output

CONCLUSION

The amount of time it takes to make a diagnosis is significantly reduced by computerized systems, reducing ophthalmologists' time and money as well as facilitating quicker patient treatment. For detecting DR at an early stage, automatic DR detection techniques are crucial. The DR phases are supported by the types of lesions that form on the retina. The most current automated approaches for classifying diabetic retinopathy that employed machine learning techniques have been evaluated in this article. Machine-learning methods are briefly introduced, and typical fundus DR datasets like STARE and DRIVE that are publically accessible have been presented. This review has also covered the practical methods that will be applied to identify and categorise DR using ML algorithms.These artificial intelligence techniques are used to predict diabetic retinopathy in patients. Knowledge is extracted for the DR prediction using ML techniques. Four different categories of machine learning models were trained to learn the outcomes. In contrast to conventional DR procedures, this text will offer simplicity, cheap cost, and great accuracy.

REFERENCES

[1] S. A. Schellini, G. M. D. Carvalho, F. S. Rendeiro, C. R. Padovani, andF. E. Hirai, ‘‘Prevalence of diabetes and diabetic retinopathy in a Brazilianpopulation,’’ Ophthalmic Epidemiol., vol. 21, no. 1, pp. 33–38, Feb. 2014.

[2] P. G. Shekelle, S. C. Morton, and E. B. Keeler, ‘‘Costs and benefits of healthinformation technology,’’ Evidence Rep. Technol. Assessment (Full Rep.),vol. 132, no. 4, pp. 1–71, 2006.

[3] C. P. Wilkinson, F. L. Ferris, R. E. Klein, P. P. Lee, C. D. Agardh, M. Davis, D. Dills, A. Kampik, R. Pararajasegaram, and J. T. Verdaguer, ‘‘Proposedinternational clinical diabetic retinopathy and diabetic macular edemadisease severity scales,’’ Ophthalmology, vol. 110, no. 9, pp. 1677–1682,Sep. 2003.

[4] M. D. Abramoff, J. M. Reinhardt, S. R. Russell, J. C. Folk, V. B. Mahajan,M. Niemeijer, and G. Quellec, ‘‘Automated early detection of diabeticretinopathy,’’ Ophthalmology, vol. 117, no. 6, pp. 1147–1154, Jun. 2010.

[5] I. Usman and K. A. Almejalli, ‘‘Intelligent automated detection of microaneurysms in fundus images using feature-set tuning,’’ IEEE Access, vol. 8,pp. 65187–65196, 2020.

[6] S. Gayathri, A. K. Krishna, V. P. Gopi, and P. Palanisamy, ‘‘Automatedbinary and multiclass classification of diabetic retinopathy using Haralickand multiresolution features,’’ IEEE Access, vol. 8, pp. 57497–57504,2020.

[7] X. Zeng, H. Chen, Y. Luo, and W. Ye, ‘‘Automated diabetic retinopathydetection basedon binocular siamese-like convolutional neural network,’’IEEE Access, vol. 7, pp. 30744–30753, 2019.

[8] M. Manjramkar, ‘‘Survey of diabetic retinopathy screening methods,’’in Proc. 2nd Int. Conf. Trends Electron. Informat. (ICOEI), May 2018,pp. 1–6.

[9] S. Qummar, F. G. Khan, S. Shah, A. Khan, S. Shamshirband, Z. U. Rehman,I.Ahmed Khan, and W. Jadoon, ‘‘A deep learning ensemble approach fordiabetic retinopathy detection,’’ IEEE Access, vol. 7, pp. 150530–150539,2019.

[10] R. G. Ramani, J. Shanthamalar J., and B. Lakshmi, ‘‘Automatic diabetic retinopathy detection through ensemble classification techniques automated diabetic retionapthy classification,’’ in Proc. IEEE Int. Conf. Comput. Intell. Comput. Res. (ICCIC), Dec. 2017, pp. 1–4.

[11] M. Ghazal, S. S. Ali, A. H. Mahmoud, A. M. Shalaby, andA. El-Baz, ‘‘Accurate detection of non-proliferative diabetic retinopathyin optical coherence tomography images using convolutional neuralnetworks,’’ IEEE Access, vol. 8, pp. 34387–34397, 2020.

[12] H. Safi, S. Safi, A. Hafezi-Moghadam, and H. Ahmadieh, ‘‘Early detectionofdiabetic retinopathy,’’ Surv. Ophthalmol., vol. 63, no. 5, pp. 601–608,2018.pp. 232–239, May 2016